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Measuring competition in microfinance markets: A new approach

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Abstract

This paper employs a relatively new method of competition measurement, the Boone indicator, in 10 vibrant microfinance markets: Bangladesh, India, Nepal, Indonesia, Philippines, Bolivia, Ecuador, Nicaragua, Mexico and Peru. This approach is able to measure competition on a yearly basis in market segments without considering the entire market as other well-known methods, for instance, the Panzar-Rosse model, requires. Stochastic frontier (SF) models have been employed to estimate the translog cost function (TCF) and then marginal costs are computed. Potential endogeneity of performance and costs are overcome by utilizing a two-step GMM estimator. Results show that competition levels vary from country to country and over the period 2003-2010 India and Nicaragua had the most competitive microfinance loan markets. Competition among the microfinance institutions in Bangladesh and Bolivia declined significantly over time, which may be due to the partial reconstitution of market power by the giant MFIs in these countries. Competition in other countries remained mostly unchanged over the years, in line with the consolidation and revitalisation of respective microfinance markets.

Keywords: Microfinance institutions, competition, panel data estimation, stochastic frontier model, the Boone indicator.

JEL Classifications: C23; C26; G21; G32.

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1. Introduction

Microfinance has recently experienced rapid and unprecedented growth in many developing countries. Both the numbers of microfinance service providers and clients served have greatly been increased (Assefa et al. 2013). Huge investment flows into microfinance operations from profitmaking sources and increased patronization and subsidized funding from governments and development agencies are the key drivers of such growth. Consequently, microfinance institutions[1] (MFIs) are now less dependent on grants, charitable money, donations, concessional funding and subsidies (Ghosh and Van Tassel, 2011). This has induced commercialisation of microfinance operations leading to increased competition amongst the MFIs for markets and to some extent to the saturation of microfinance services. But providing retail financial services among the low-income clients is still a vast potential market (CGAP, 2005), which increasingly attracts the profit-oriented commercial banks to enter the market (Assefa et al., 2013). This helps competition to increase further. However, since MFIs normally operate in places which are little penetrated by commercial banks, competition in microfinance is particularly increased with MFIs' growing commercialization of operations (Cull et al., 2009b) if not through direct penetration of commercial banks.

Interests in studying competitive conditions in microfinance markets are scant. So, literature on the consequences of competition in microfinance is not very rich. Also the results of a small number of studies conducted before remained ambiguous. For instance, Motta (2004) argued that increased competition generally contribute to reducing production costs, lowering prices of goods and services and also to developing new products and efficient technologies. Assefa et al. (2013) claimed that MFIs are to expect similar benefits of competition. However, increased competition in microfinance by and large did not bring much positive impacts per se. For example, McIntosh and Wydick (2005) claimed that competition may lower the borrower selection standards, weaken bank-customer relationships and enhance multiple borrowing and loan defaults. Schicks and Rosenberg (2011) supports this view by arguing that MFIs' outreach and loan portfolio performance in general have declined due to competition and clients are now more prone to over-indebtedness and falling into the situation of debt-trap. Again, apart from these ambiguities, there is little empirical evidence currently available to estimate the influence of growing competition on the price and quality of loan products and on the financial soundness of micro-lenders. Also, we know very little on the yearly growth of competition in different markets. Therefore, it is crucial to explore the degrees, causes and consequences of competitiveness, or the likely presence of anti-competitive behaviour and inefficiency, in different microfinance markets as they might impose severe costs on respective markets later. For instance, higher competition may deepen the concerns for mission drift in microfinance since too much market power negatively affects clients' access to financial services[2].

It is difficult to measure competition applying any direct approach as data on costs and prices of banking products are usually unavailable (Leuvensteijn et al., 2011). So, many indirect measures of competition have been in use in the banking literature. In microfinance literature, a recent study of Assefa et al. (2013) has used the Lerner index to measure competition. Baquero et al. (2012) constructs the yearly Herfindahl–Hirschman indices in attempt to capture the changing competitive environment in microfinance. Mersland and Strom (2012) measured competition by employing the Panzar-Rosse revenue tests in static and dynamic versions. But, these measurers have their own limitations and may not appropriately measure competitiveness especially in loan markets where interest rate regulations are in place[3] (Xu et al., 2013). Microfinance operations are increasingly regulated these days. So, quite reasonably we need to employ a relatively better approach for studying competitive conditions in microfinance markets.

The 'profit elasticity' (PE), or the Boone, indicator is a relatively improved measure of competition. Founded on the 'relative profit differences' (RPD) concept, and essentially as an elaboration on the efficiency hypothesis, the PE indicator is based on the idea that competition rewards efficiency (Boone, 2008). The underlying intuition is that in a more competitive market, firms are punished more harshly (in terms of profits) for being inefficient. The PE indicator has several advantages. First, it measures competition not only for the entire country's microfinance market, but also for the concerned MFIs' product markets (e.g., loan market). Second, unlike the Bresnahan (1982) model the approach is less data-intensive. Third, differences in MFI legal types (e.g., non-profit NGO, non-bank financial institution, village bank etc.) should not matter while estimating this indicator. Fourth, the approach allows for the estimation of yearly competition measures to assess developments over time, while ignores differences in product quality, design and the attractiveness of innovations (Leuvensteijn et al., 2011). All in all, the PE indicator is more robust from theoretical as well as empirical point of views. It is in this context this paper uses the PE indicator as a relatively new and better measure of competition. Applying this measure for the banking sector Schaeck and Cihák (2010), Boone and Leuvensteijn (2010) and Leuvensteijn et al. (2011), for instance, provide a more explicit empirical validation.

However, despite the above advantages and the recent interests in studying the impacts of competition in microfinance, no study so far has employed the Boone indicator to explore the competitive conditions in different microfinance markets. By introducing this indicator to microfinance data this paper contributes to the empirical literature on microfinance competition. Numerous MFIs used to function as monopolists before they were commercialized (CGAP, 2001; McIntosh et al., 2005) with potential allocative and technical inefficiencies leading to welfare losses. But MFIs now generally follow similar business practices, grant small loans to unbanked poor customers and small business enterprises and normally the repayment period is less than a year. Against a backdrop of recent changes in the microfinance competitiveness, now MFIs are on average monopolistically competitive so changes in lending rates, total revenue and profitability are the results of increased input prices (Mersland and Strom, 2012). All of these traits are appropriate for applying the Boone indicator for measuring competition in the market.

The paper will contribute to the literature in many ways. First, the analysis will provide an empirical investigation of the differing levels of competition in selected microfinance markets. Second, to contribute methodologically, estimates of the degree of competitiveness have been obtained through panel data estimations, by which we can take care of the dynamic and reforming microfinance market landscapes under scrutiny and their varying regulatory environments. Thus, the short-run dynamics in the data can be handled and the inference problems linked with non-stationary data are solved. In terms of originality, the study will contribute to the microfinance, banking and industrial organization literature at least in three ways. First, this is one of the first attempts to use the Boone indicator in microfinance data. We extend the definition of competition and move beyond common measures of competition for example the Lerner's index, the Panzar-Rosse H-statistics and the Herfindahl-Hirschman index (HHI) as used in other studies. Second, the global dataset used in this study has observations on a large number of MFIs over a longer period. Third, results of this exercise can be used in other studies on competition and industrial organisation. Results show that India and Nicaragua had the most competitive microfinance loan markets over the period 2003-2010. Competition among the MFIs in Bangladesh and Bolivia declined significantly over this time period, which may be due to the partial reconstitution of market power by the giant MFIs in these countries. Competition in other countries remained mostly unchanged over the years, in line with the consolidation and revitalisation of respective microfinance markets.

The paper is organised as follows. Section 2 presents a brief review of literature on different approaches to measure competition in microfinance. Section 3 explains the Boone indicator model as a new measure of competition. The data are described in section 4. The econometric method and the results are presented in Section 5. Finally, Section 6 concludes the paper.

2. Measuring competition in microfinance

As noted earlier, at least two recent developments over the last few years have induced increased competition in microfinance. First, both the number of microfinance clientele and the number of MFIs have increased very rapidly because of subsidized funding and supportive activities of governments and development agencies and diversification of funding sources including welcoming funding from commercial sources. The popularity of the self-sustainability model of microfinance operation has also driven MFIs to shift their focus on funding from the commercial sources. Second, the number of for-profit commercially-oriented MFIs has increased alongside. To function properly, MFIs largely depend on soft-information and useful client-institution links. These mainly help solving the information asymmetry problems pervasively active in the context of credit allocation. However, increased competition among the MFIs led by these recent developments have affected MFIs' activities in a variety of ways and hindered them functioning properly as described below.

The socially-oriented MFIs and their clients are particularly affected by increased competition. A higher level of competition in general exacerbates moral hazard and information asymmetry in the industry. Setting-up a theoretical model, McIntosh and Wydick (2005) argue that competition reduces the ability of MFIs to cross-subsidize and increases asymmetric information on borrower quality. As a result, impatient borrowers become keen to acquire multiple loans, over-indebtedness increases and repayment rates decrease. Increased competition also induces the profitable and productive clients of the socially-motivated MFIs to shift to the profit-oriented MFIs. Such transfer eventually worsens the loan-portfolio quality of the socially-motivated MFIs and negatively impacts their cross-subsidisation[4] possibilities (Navajas *et al.*, 2003; McIntosh and Wydick, 2005; Vogelgesang, 2003). Schicks and Rosenberg (2011) found similar results. They claim that, through its impacts on the clients, increased competition in microfinance creates information asymmetry in the industry coupled with repayment problems of the borrowers leading to the risk of over-indebtedness, debt-traps and increased sociological and psychological constraints. McIntosh, Janvry and Sadoulet (2005) argue that repayment performance of borrowers may worsen and the amount of savings deposited with the village bank may reduce as a result of increased competition. However, Baquero et al. (2012) finds that for-profit MFIs charge significantly lower loan rates and demonstrate better portfolio quality in less concentrated markets. But nonprofit MFIs are comparatively insensitive to changes in concentration. In saturated markets, MFIs try to maintain their customer base and decrease their costs by lowering lending standards or decreasing screening efforts (Schicks and Rosenberg, 2011) thus leading to higher loan defaults due to the increase of risky borrowers. Regarding outreach performance, Assefa, Hermes and Meesters (2012) argue that intense competition is negatively associated with MFI performance measured by outreach, profitability, efficiency and loan repayment rates. Hartarska and Nadolnyak (2007) and Lensink and Meesters (2008) also confirm that increased competition has a negative impact on outreach. To summarize, increased competition in microfinance thus affects the MFIs and their clients in at least two ways. First, increased competition leads to a decline in the borrower quality as better performing clients move to profit-oriented MFIs. Consequently, loan defaults rise. Second, with increased competition the interest rates drop, resulting in lower profitability and less cross-subsidisation.

Due to data unavailability, however, it is generally difficult to apply direct methods to estimate the degree of competitiveness of a market (Leuvensteijn et al. 2011). So, there are clear differences in terms of techniques applied and several indirect methods have been used for measuring competition in banking and microfinance markets. The stream of literature on this topic can be divided into two major approaches: the structural (or, industrial organization—IO) approach and the non-structural (or, new empirical industrial organization—NEIO) approach. The structural method, originated from the industrial organisation theory, proposes tests of market structure to assess competition on the basis of the 'structure conduct performance' (SCP) paradigm. The SCP hypothesis argues that greater concentration causes less competitive conducts and leads to greater profitability. This hypothesis assumes that market structure affects competitive behaviour and, hence, performance. Also, especially in the banking literature, many articles test this model jointly with an alternative explanation of performance, namely the efficiency hypothesis, which attributes differences in performance (or profit) to differences in efficiency (e.g. Goldberg and Rai, 1996). The SCP method uses concentration indices such as the n-firm concentration ratios or the Herfindahl-Hirschman index (HHI) as proxies for market power. In microfinance literature, among others, Baquero et al. (2012) employed the HHI to measure competition in microfinance markets covering data from 379 MFIs located in 69 countries over the period 2002-08. To measure competition, Olivares-Polanco (2005) used data from 28 Latin American MFIs and employed the percentage of concentration of the largest MFIs by country, where concentration denotes the market share held by the largest MFIs in a country.

Nevertheless, the structural approach has several deficiencies (Hannan, 1991). Although the SCP paradigm and the efficiency hypothesis have frequently been employed in empirical research, they lack proper support from the microeconomic theory (Bikker and Haaf, 2002; Claessens and Laeven, 2004; Delis et al., 2008; Coccorese, 2009). As a result, the non-structural (or, the NEIO) approaches are increasingly being used in recent times which, from the estimated parameters of equations, draw inferences on the observed behaviour (Lau, 1982; Bresnahan, 1982; Panzar and Rosse, 1987; Carbo et al., 2009). While the structural measures infer the degree of competition from indirect proxies such as market structure or market shares, non-structural methods measure the conduct directly. Within this framework, requiring detailed data though, the simultaneous-equation approach calculates competition by simultaneously estimating supply and demand functions. Among others, the Panzar-Rosse revenue tests (PR-RT) (Panzar and Rosse, 1987)—which provides an aggregate measure of competition—requires easily available data on MFI-specific variables only. The PR-RT checks whether the input and output prices move in harmony or they move disproportionately (Xu et al., 2013). But, the Lerner index—an individual measure of market power—views that high profit may indicate a lack of competition. In that sense market power is related to profitability. Thus the Lerner index uses the 'price cost margin' (PCM), i.e., the mark-up in output prices (P) above marginal cost (MC) (Xu et al., 2013). In other words, market power equals (P–MC)/P. The PCM is usually taken as an indicator of market power because the larger the margin, the larger the difference between price and marginal cost. In their recent study, Assefa et al. (2013) applies a Lerner index to measure competition in microfinance and the study is based on data from 362 MFIs in 73 countries for the period 1995–2008. Mersland and Strom (2012) apply the Panzar-Rosse model to microfinance data from 405 MFIs in 73 countries covering 1998-2010.

Among other measures of competition used in the microfinance literature, Vogelgesang (2003) uses the fraction of clients of the bank with concurrent loans from other MFIs. In McIntosh et al. (2005), competition is measured in terms of the number, presence and proximity of competitors providing group loans at the lending group level. Using data from 342 MFIs located in 38 countries, Cull et al. (2009a) measures competitive pressure by using bank penetration variables such as the number of bank branches per capita and per square kilometre. This is, however, a country-level measure of competition. Thus we see that although previous studies have used different competition indicators such as the Lerner index, the PR H-statistics, the HHI etc., no study has employed the less-data-intensive Boone indicator for measuring competitiveness of microfinance markets.

3. Measuring competition: The Boone indicator model

The Boone (2008) model[5] considers the impact of efficiency on performance in terms of profits and market shares centring on the idea that more efficient firms (firms with lower marginal costs) gain higher market shares or profits. The higher the degree of competition in the market the stronger the impact and the more negative the indicator. Quite intuitively, competition improves the performance of efficient firms and weakens the performance of inefficient firms. The Boone model has at least two advantages. First, products are assumed close substitutes with no or low entry costs which is an advantage over the concentration measures and some other competition proxies. Second, the Boone indicator measures competition for specific product markets and different categories of financial institutions. Following Schaeck and Cihak (2010) and Leuvensteijn et al. (2013), the following model defines the Boone indicator as follows:

$$\ln \pi_{it} = \alpha + \sum_{t=1}^{T} \beta_t \, ln(MC_{it}) + \sum_{t=1}^{T-1} \alpha_t d_t + \mu_{it} \qquad (1)$$

where π_{it} stands for profit of MFI i at year t, MC is the marginal costs of MFI i at year t, β denotes the Boone indicator and d_t is the time dummy. The above specification evaluates the competitive conditions for each microfinance market included in the dataset for the entire period. We add the time dummies to control for timely evolution of the profits within a country. We expect that MFIs with low marginal costs gain higher profits, i.e. $\beta < 0$. Competition tends to increase this effect, since more efficient MFIs outperform less efficient ones. The more negative β is, the higher is the competition level in a market. However, positive values for β means that the more marginal costs a bank has the more profits it will earn (Leuvensteijin et al., 2011) signifying the presence of extreme level of collusion or competition on quality (Tabak et al., 2012).

The Boone model also provides the yearly estimates of competition to let us examine the evolution of competition every year. So, we introduce one time-dependent interaction variable of the Boone Indicator and the time dummies. We estimate the yearly Boone scores from the following equation where the individual time dummies are to capture the year-specific factors common to all MFIs in the market:

$$\ln \pi_{it} = \alpha_0 + \sum_{t=1}^{T} \beta_t d_t \, ln(MC_{it}) + \sum_{t=1}^{T-1} \alpha_t d_t + \mu_{it} \qquad (2)$$

Where, explanations for all the variables and coefficients are similar to equation (1). We use ROA (return on assets) as a proxy for profits[6] and following Leuvensteijn et al (2011), marginal costs (MC_{it}) for each MFI and year in the database have been estimated from a separate translog cost function (TCF) as marginal costs are not observed directly[7]. We then use the MC as an explanatory variable both in (1) and (2). In the translog cost function we include one output and three variables for input costs: cost of labour, cost of funds and cost of capital. Gross loan portfolio is used as a proxy for output. Costs of three inputs have been proxied respectively by the ratio of personnel expenses to total assets, the ratio of financial expenses to total assets and the ratio of administrative expenses to total assets. We impose symmetry and linear homogeneity restrictions in input prices. Linear homogeneity means that costs will increase (decrease) by the same proportion as the costs of inputs increase (decrease). Hence, intuitively, the total costs represent the three inputs included in the cost function. Thus, we define the TCF as follows:

$$\ln TC_{it} = \alpha_0 + \delta_0 \ln q_{it} + \frac{\delta_1}{2}(\ln q_{it})^2 + \sum_{j=1}^{3} \alpha_j \ln W_{jit} + \ln q_i \sum_{j=1}^{3} \alpha_j \ln W_{jit}$$
$$+ \frac{1}{2}\sum_{j,\, k=1}^{3} \alpha_{jk} \ln W_{jit} \ln W_{kit} + \sum_{t=1}^{T-1} \alpha_t d_t + \varepsilon_{it} \qquad (3)$$

where TC_{it} stands for total costs (captured by the total expenditures over assets ratio) of MFI i at year t, q_{it} represents output of MFI i at year t captured by the gross loan portfolio, W denotes the three input prices and ε_{it} is an error term. Time dummies (d_t) for each year are also included to capture the technological progress over time.

Previous studies (see, for example, Leuvensteijn et al., 2011) have employed the ordinary least squares (OLS) to estimate the parameters of the cost function. However, employing OLS may have several limitations including producing biased parameter estimates resulting from the multicollinearity problem since the TCF includes a large number of explanatory variables. Recently, stochastic frontier (SF) models have become a popular tool for efficiency analysis. Theoretical motivation of the SF model is that no economic agent can exceed the ideal “frontier" and the deviations from this extreme represent the individual inefficiencies. The parametric SF models characterize a regression model (estimated by likelihood-based methods) with a composite error term that includes the classical idiosyncratic disturbance and a one-sided disturbance which represents inefficiency (Belotti et al., 2012). Thus, as an alternative, this paper uses a parametric SF model to estimate the translog cost function. We use the specification of the TCF in logarithmic form as it allows interpreting the first-order coefficients as cost elasticities.

The marginal cost of MFI i at year t can then be obtained from the first derivative of equation (3) as follows:

$$MC_{it} = \frac{\partial TC_{it}}{\partial q_{it}} = \frac{TC_{it}}{q_{it}}\left(\delta_0 + \delta_1 \ln q_{it} + \sum_{j=1}^{3} \delta_{j+1} \ln W_{j,it}\right) \qquad (4)$$

Leuvensteijin et al. (2011) and Schaeck and Cihak (2010) suggest potential endogeneity problems in the estimation of equations (1) and (2) as performance and costs are determined simultaneously[8]. So, based on the endogeneity tests we either utilize a two-step GMM estimator, where we use first lag of MC_{it} as the instruments, or we choose to use a fixed-effects model (i.e., the within estimator) to estimate the models. The marginal costs are computed by substituting parameter estimates from TCF into equation (4).

4. Data

MFI-level financial, portfolio and outreach performance data were obtained from individual MFI profiles voluntarily reported to the MIX Market database, the most detailed publically available database so far. Initially, data were collected for the period 1996 to 2010 from 1144 MFIs operating in 35 countries (in total, 7146 observations). These MFIs are of all legal types—non-profit NGOs, non-bank financial institutions (NBFIs), banks, rural banks, cooperatives/credit unions and others. However, not all of them could be utilized in the exercise. The selection criteria for MFIs were mostly based on the available amount and quality of the data. After careful verification of the data and excluding MFIs and/or periods with missing, negative or zero values for variables of our interest, resulting sample for estimating the Boone indicator is an unbalanced panel of 521 MFIs of 10 countries. The countries are Bangladesh, India, Nepal, Indonesia, Philippines, Bolivia, Ecuador, Mexico, Nicaragua and Peru. As required, ten separate panel datasets have been created corresponding to the microfinance sectors in each of these countries. In the datasets, MFIs report information for 3-8 years. The MIX Market uses 'diamonds' to rank the MFI-data quality on a scale of 1 to 5, where 5-diamonds imply the best quality. To ensure high quality data, in the datasets we mostly kept MFIs with at least a level-3 (3-diamonds) disclosure rating on the MIX market. However, to avoid any potential bias in sample selection we also included 28 observations on MFIs which have less than level-3 disclosure rating[9]. Besides, as two time lags have been used in several estimations, the database finally reduces 3001 observations from 2003 to 2008. The sampled MFIs have been distributed among all six developing regions in the world—East Asia and the Pacific (EAP), Eastern Europe and Central Asia (EECA), Latin America and the Caribbean (LAC), Middle East and North Africa (MENA), South Asia (SA) and Sub-Saharan Africa (SSA)[10].

These countries have been selected for a number of reasons. First, the study attempts to cover regional differences in the level of competition. So, the sampled countries come from three different developing regions with vibrant presence of microfinance operations: South Asia, East Asia and the Pacific and Latin America and the Caribbean. These countries have potential differences in their regulatory frameworks too. Also, the revenue streams of MFIs in these regions vary from country to country depending on their product portfolio mix. For example, Indonesian MFIs largely generate revenues from micro-savings. Whereas, in India MFIs mostly rely on microloans for their revenue generation. So, seemingly these two microfinance industries have different types of revenue streams and they are difficult to compare. But as we are employing the Boone indicator to measure competition, differences in country-specific revenue sources do not matter much. Thus we can compare the revenue stream of a ‘micro-saving’ centric country (Indonesia), for instance, with that of a ‘microloan’ centric country (India). Second, in this study countries where the microfinance sectors are getting increasingly competitive and characterized by differing levels of concentration have been chosen. Third, these countries are of varying magnitudes of population, GDP and footprint of the microfinance sectors. For example, India is one of the biggest countries in the world, with a population of around 1.27 billion in 2013, as well as a country boasting several big MFIs in the world. On the contrary, for instance, Ecuador and Peru are much smaller than India having population of only 15.4 million and 30.4 million respectively.

Table 1 provides the descriptions of the variables used in the analysis. Table 2 and Table 3 present number of observations by country, MFI legal types and year. Table 4 presents the summary statistics of the MFI-level output and input price variables used in the translog cost specification by countries. Evidently, MFIs from Bangladesh, Bolivia, Mexico and Peru generally have the largest loan portfolios. In contrast, the smallest micro-financing systems in terms of loans are those from Indonesia, Nepal and Philippines.

5. Estimation Results of the Boone Indicator

5.1. Degree of competition in microfinance across countries

This section discusses the full sample period estimates of the Boone indicator. In Table 5, as evident from the summary statistics of the Boone scores, our data include MFIs that are practically highly competitive (negative Boone-score) and those that are collusive (positive values for the Boone indicator). Table 5 presents averages of the Boone indicator over 2003–2010 by country. The results suggest that competition in the sampled microfinance markets varies considerably. We observe that the microfinance loan market in Bangladesh is the most competitive. Also, the loan markets in India and Nicaragua were among the best competitive markets within the sampling period. However, as we can see from the minimum and maximum values, competition levels have changed significantly over time in all sampled countries other than in Peru and Indonesia. Again, the microfinance loan markets of Indonesia, Philippines, Peru and Nepal were generally less competitive. To explain these dissimilar levels of competition we now turn to the yearly estimations of the Boone indicator as presented in Table 6.

Note that, the Boone indicator is now time dependent. While the above conclusions based on the full sample period estimates generally remain valid, there are some notable differences across countries in the Boone indicator's development over the years. Across countries, not all the yearly Boone indicators differ significantly from zero. As expected, the value of β_t is in some cases positive (instead of being always negative) in all of the sampled countries. Table 6 shows that the betas do not differ significantly from zero in several cases and this is true for all the years and all the countries in the sample. For Bangladesh, India, Bolivia, Nicaragua and Mexico, we observe considerable jumps in the series over time (see also Figure 1 and Figure 2). However, the estimated successive annual betas for each country do not differ significantly from each other. Other than Bangladesh and Nepal, all other countries in the sample show positive β_t values for varying number of years instead of the expected negative values which is consistent with the rationale provided for eq. (2) before.

Estimates suggest that currently (in year 2010) the microfinance sectors in India and Nicaragua are among the most competitive ones. In the beginning of the sampling period the microfinance industries in these countries were not very competitive, but over the years they have become so. Most likely, this result for India and Nicaragua hinges in part on the special structure of their microfinance regulatory system. For example, a large number of Indian MFIs is of non-bank financial institution (NBFI) status and they are equally regulated and competing with almost equal footing. Thus, the competitive environment of these NBFIs operating countrywide has possibly been reflected in the Boone indicators for the Indian MFIs.

5.2. Developments in competition over the years

Recently the microfinance sector in Bangladesh went through a process of regulation which is likely to have had a catalytic effect on competition, as our estimates suggest strong competition in 2003. In more recent years, however, the giant Bangladeshi MFIs may have been able to reconstitute some market power as our results point to a continuous decline in competition since 2003. A similar declining trend in competition is also seen in the Bolivian microfinance market (see Figure 2).

Our estimates of the Boone indicator for the Indian and Nicaraguan microfinance markets show a significantly increasing trend over the years under scrutiny. This gradual increase in competition may be due to the decrease in market share of the giant MFIs in respective countries. In India, competition among the microfinance service providers seems to have improved significantly (see Figure 1). This remarkable increase can be partly attributed to a history of no or very little competition in 2003. In particular, our estimates show that the Indian microfinance sector experienced a rather marked transformation from a climate with very little competition in 2003 to a more competitive environment in recent years. This partly reflects the process of financial deregulation and the gradual resolution of the bad loan problems that plagued the industry recently. Also, profound and structural changes in the Indian microfinance industry have helped to foster a competitive environment. An increasing trend in competition is also seen in the Nicaraguan microfinance sector. Again, as Figure 3 shows, the degree of competitiveness in the microfinance sectors in other sampled countries remained mostly the same over the years (2003-2010). One plausible explanation for this outcome is that the regulatory environment did not change much to affect the overall competition scenarios in these countries.

6. Conclusions

This paper uses a new measure for competition, the Boone indicator, and is the first study that applies this approach to the microfinance markets. This indicator quantifies the impact of marginal costs on performance, measured in terms of return on assets. Instead of approximating marginal costs by average variable costs, this paper calculates the marginal costs from the estimated translog cost function by employing the stochastic frontier approach (SFA). Finally, these marginal cost estimates have been used to compute the Boone indicators. Although the approach is not beyond limitations, especially since MFIs are still subsidy-dependent in many cases and their products are not necessarily always similar, this approach has the advantage of being able to provide the yearly observations microfinance in a market segment. Other well-known measures of competition, e.g., the PR-RT, consider only the entire market. Moreover, estimation method of the Boone indicator is less data intensive.

The study employs the Boone indicator to 10 vibrant microfinance markets. Results show that during the period under scrutiny the degree of competitiveness of the sampled microfinance markets vary significantly. Overall, the microfinance markets in India and Nicaragua were among the best competitive. Competition among the MFIs in Bangladesh and Bolivia declined significantly over time, which may be due to the partial reconstitution of market power by the giant MFIs in these countries. Competition in other countries remained mostly unchanged over the years, in line with the consolidation and revitalisation of respective microfinance industries.

All in all, as the estimated Boone indicators show, competitive conditions in the microfinance markets and their developments over time differ considerably across countries. These differences seem largely to reflect the distinct characteristics of respective microfinance sectors, such as the relative importance of and changes to the MFIs' institutional and regulatory environments during the period under scrutiny.

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Notes

1. However, some studies (e.g., D'Espallier et al., 2013) claim that despite increased commercialisation of microfinance, subsidies still play an important role in MFIs' operations and around 95% of them depends on subsidised funding to cover costs and finance loans.
2. The concerns for mission drift in microfinance are at the heart of recent debates on the future of microfinance. Discussions on this, however, are beyond the scope of this article. For a detailed and focused discussion on this issue, see for example, Mersland and Strom (2010), Kar (2013), Armendariz and Szafarz (2011) and Armendariz et al. (2011).
3. See, for example, Xu et al. (2013) for a detailed discussion on why conventional indicators such as the Lerner index and Panzar-Rosse H-statistic fail to measure competition in loan markets properly due to the system of interest rate regulation.
4. Cross-subsidisation means reaching out to the wealthier clients to finance a larger number of poor clients having smaller average loan size.
5. Discussions in this section as well as part of the literature reviews used in this paper follow the discussions in Kar and Bali Swain (2014). Tabak et al. (2012), for example, presents a literature review on the studies that employ this method. In addition, Bikker and Spierdijk (2008) provide a detailed discussion on this measure and on competition in the financial sector.
6. The dependent variable is computed as log ($1+ROA_{it}$) just to avoid negative values of return on assets in the log specification.
7. Total costs are the sum of personnel expenses, other non-interest expenses, and interest expenses.
8. Schaeck and Cihak (2010) approximate a firm's marginal costs by the ratio of average variable costs to total income.
9. This study sampled MFIs which have: 5-diamonds (20.96%), 4-diamonds (42.09%), 3-diamonds (36.02%) less than 3-diamonds (0.93%).
10. These regional classifications are according to the World Bank.

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Table 1: Description and definition of variables

Variable name	Description
Total costs	Total expenditures over total assets ratio (normalised by one of the input prices: price of labour)
Boone indicator	A proxy for competition; The absolute value of the β_t in equation (2).
Output	Proxied by gross loan portfolio
Unit price of labour	Ratio of personnel expenses to total assets. Personnel expenses include wages and salaries, social security contributions, contributions to pension funds, and other staff-related expenses.
Unit price of funds	Ratio of interest expenses to total intermediated funds (current accounts, savings accounts, time deposits, repurchase agreements, as well as alternative funding sources such as retail bonds).
Unit price of physical capital	Ratio of administrative expenses to total assets. Administrative expenses include rents, service charges, security, information systems and communications, other office and insurance expenses, professional charges, publicity and advertising, and depreciation.

Notes: Variable price of labour (proxied by personnel expenses to total assets) is used to normalise the total expenditure, output (proxied by gross loan portfolio) and three input price variables used in the analysis. All of these variables were first adjusted by their respective median values.
The MFI-level yearly financial data were collected from the MIX for 2003-2010.

Table 2: Number of observations by country and year

Country/Year	2003	2004	2005	2006	2007	2008	2009	2010	Total
Bangladesh	43	53	54	36	32	29	28	27	302
Bolivia	11	18	20	25	24	23	23	23	167
Ecuador	24	19	35	43	46	47	43	40	297
India	31	67	73	79	68	80	78	71	547
Indonesia	21	23	25	40	40	31	18	16	214
Mexico	5	8	26	33	45	41	39	39	236
Nepal	15	22	26	33	33	32	28	27	216
Nicaragua	19	24	25	24	25	26	25	23	191
Peru	31	42	45	50	58	60	58	57	401
Philippines	36	55	60	61	61	61	57	39	430
Total	236	331	389	424	432	430	397	362	3001

Table 3: Number of observations by country and MFI legal types

Country name	Legal type						
	NGO	NBFI	Bank	RB	CU-Coop	Others	Observations
Bangladesh	289	0	8	0	5	0	302
Bolivia	93	38	24	0	12	0	167
Ecuador	101	0	32	0	164	0	297
India	259	223	6	8	40	11	547
Indonesia	25	0	0	165	17	7	214
Mexico	35	178	12	0	11	0	236
Nepal	63	42	19	44	48	0	216
Nicaragua	140	14	14	0	23	0	191
Peru	124	218	8	0	51	0	401
Philippines	177	0	13	234	6	0	430
Observations	1306	713	136	451	377	18	3001

Table 4: Mean and standard deviations of output and prices of inputs employed in the translog cost function

Country	GLP	AEA	FEA	PEA
Bangladesh	4.36e+07	0.038	0.038	0.089
	(1.32e+08)	(0.033)	(0.021)	(0.027)
Bolivia	5.48e+07	0.056	0.043	0.074
	(9.22e+07)	(0.029)	(0.018)	(0.034)
Ecuador	1.99e+07	0.066	0.042	0.074
	(4.68e+07)	(0.051)	(0.022)	(0.052)
India	2.66e+07	0.050	0.077	0.060
	(9.29e+07)	(0.060)	(0.031)	(0.051)
Indonesia	6264720	0.054	0.082	0.076
	(3.89e+07)	(0.044)	(0.038)	(0.063)
Mexico	6.00e+07	0.151	0.064	0.208
	(1.91e+08)	(0.076)	(0.038)	(0.119)
Nepal	2736937	0.025	0.054	0.051
	(3527610)	(0.023)	(0.015)	(0.027)
Nicaragua	1.45e+07	0.090	0.063	0.097
	(2.57e+07)	(0.053)	(0.033)	(0.051)
Peru	6.14e+07	0.075	0.061	0.099
	(1.33e+08)	(0.040)	(0.026)	(0.067)
Philippines	6770964	0.095	0.043	0.120
	(9618705)	(0.044)	(0.018)	(0.083)

Note: Standard deviations are in the parentheses. GLP: Gross loan portfolio, in US $; AEA: Administrative expenses to total assets ratio; FEA: Financial expenses to total assets ratio; PEA: Personnel expenses to total assets ratio.

Table 5: Summary statistics of the Boone indicator for various countries (2003-10)

Country	Observations	Mean	Median	St. Dev.	Min.	Max.
Bangladesh	302	-0.033	-0.031	0.015	-0.059	-0.011
Bolivia	167	-0.008	0.001	0.021	-0.050	0.020
Ecuador	297	-0.008	-0.001	0.013	-0.038	0.006
India	547	-0.011	-0.009	0.031	-0.058	0.035
Indonesia	214	0.003	0.005	0.012	-0.019	0.017
Mexico	236	0.002	-0.0004	0.028	-0.035	0.109
Nepal	216	-0.008	-0.007	0.005	-0.016	-0.0004
Nicaragua	191	-0.025	-0.026	0.038	-0.091	0.018
Peru	401	-0.006	-0.012	0.012	-0.018	0.024
Philippines	430	-0.008	-0.009	0.005	-0.014	0.001
Total	3001	-0.010	-0.010	0.023	-0.091	0.109

Note: Author’s own calculations from the MIX data.

Table 6: Developments of the Boone scores over time for various countries

Year/Countries	Bangladesh Boone	India Boone	Nepal Boone	Indonesia Boone	Philippines Boone
2003	-0.029	0.009	-0.013	-0.009	-0.013
	(-0.24)	(0.04)	(-0.64)	(-0.55)	(-1.06)
2004	-0.009	0.040	-0.009	0.007	0.001
	(-0.18)	(0.30)	(-0.36)	(0.27)	(0.15)
2005	-0.044	-0.003	-0.017	0.008	-0.008
	(-1.56)	(-0.06)	(-0.53)	(0.48)	(-1.43)
2006	-0.007	0.019	-0.001	0.006	-0.009
	(-0.63)	(0.52)	(-0.06)	(0.71)	(-1.47)
2007	-0.008	0.041	-0.005	0.018*	-0.009
	(-0.64)	(1.18)	(-0.44)	(2.03)	(-1.84)
2008	-0.034**	-0.008	-0.011	0.018	-0.002
	(-3.06)	(-0.33)	(-0.95)	(2.46)	(-0.32)
2009	-0.044**	-0.047	-0.007	-0.012	-0.011
	(-2.96)	(-1.85)	(-0.71)	(-0.99)	(-1.72)
2010	-0.039**	-0.052	-0.005	-0.015	-0.014
	(-3.29)	(-1.76)	(-0.52)	(-0.96)	(-1.68)

Note: Time dummies were included in regressions, but the coefficients are not shown. In the parentheses, t-values have been reported. Statistically significant at the *10%, **5% and ***1% levels.

Table 6: Developments of the Boone scores over time for various countries (continued)

Year/Countries	Bolivia	Ecuador	Mexico	Nicaragua	Peru
	Boone	Boone	Boone	Boone	Boone
2003	-0.036	-0.011	-0.035	0.007	0.004
	(-0.86)	(-0.91)	(-0.37)	(0.14)	(0.29)
2004	-0.004	-0.045**	0.109	-0.001	0.024*
	(-0.18)	(-3.43)	(0.42)	(-0.03)	(2.23)
2005	-0.017	-0.014	0.039	-0.035	-0.011
	(-1.63)	(-1.73)	(0.53)	(-0.70)	(-1.46)
2006	-0.021	-0.029**	-0.022	-0.026	-0.013
	(-1.64)	(-3.65)	(-0.66)	(-0.64)	(-1.94)
2007	-0.018	-0.018	0.013	-0.003	-0.014
	(-1.27)	(-1.90)	(0.36)	(-0.09)	(-1.82)
2008	0.004	-0.005	-0.000	-0.019	-0.016
	(0.38)	(0.92)	(-0.01)	(-0.64)	(-1.88)
2009	0.011	0.003	-0.018	-0.073**	-0.004
	(1.01)	(0.24)	(-0.62)	(-2.71)	(-0.65)
2010	0.017*	-0.004	-0.011	-0.084***	-0.019*
	(2.31)	(-0.32)	(-0.39)	(-3.31)	(-2.49)

Note: Time dummies were included in regressions, but the coefficients are not shown. In the parentheses, t-values have been reported. Statistically significant at the *10%, **5% and ***1% levels.

Figures

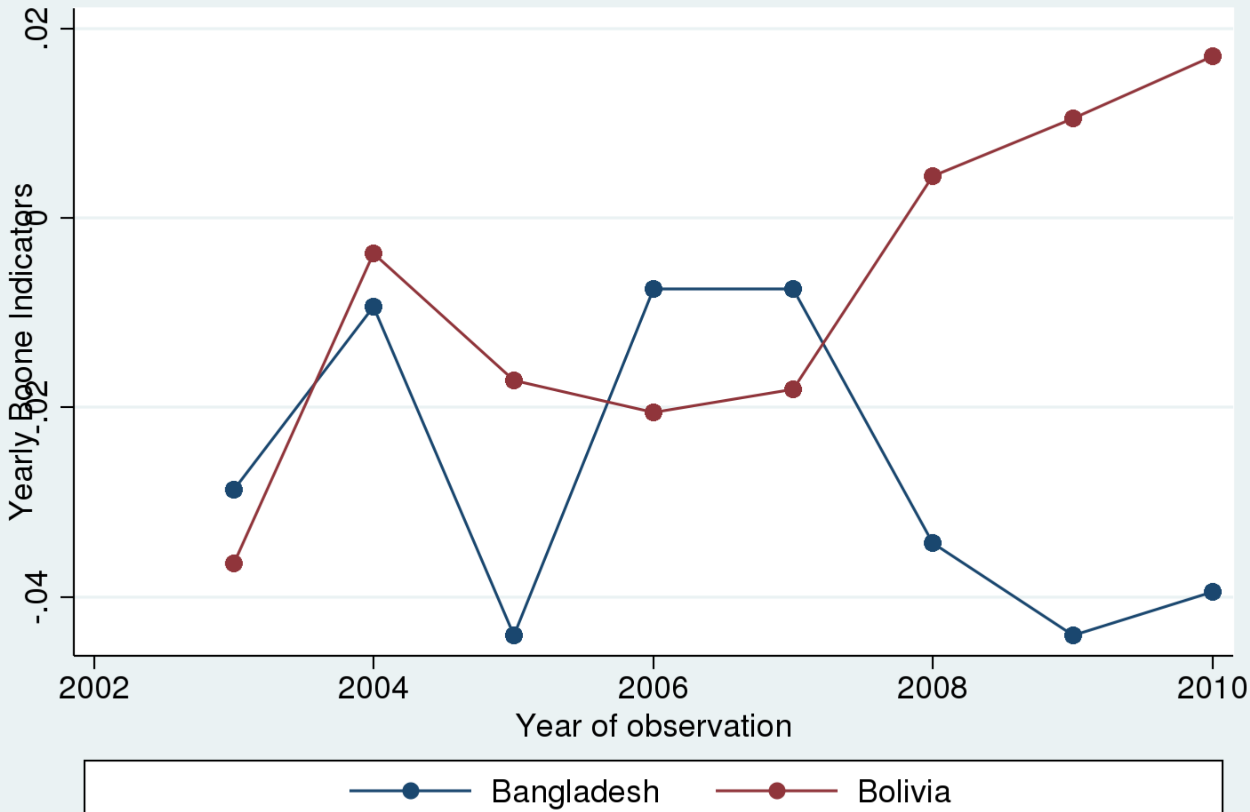

Figure 1: Boone indicators of the countries showing decreased competition

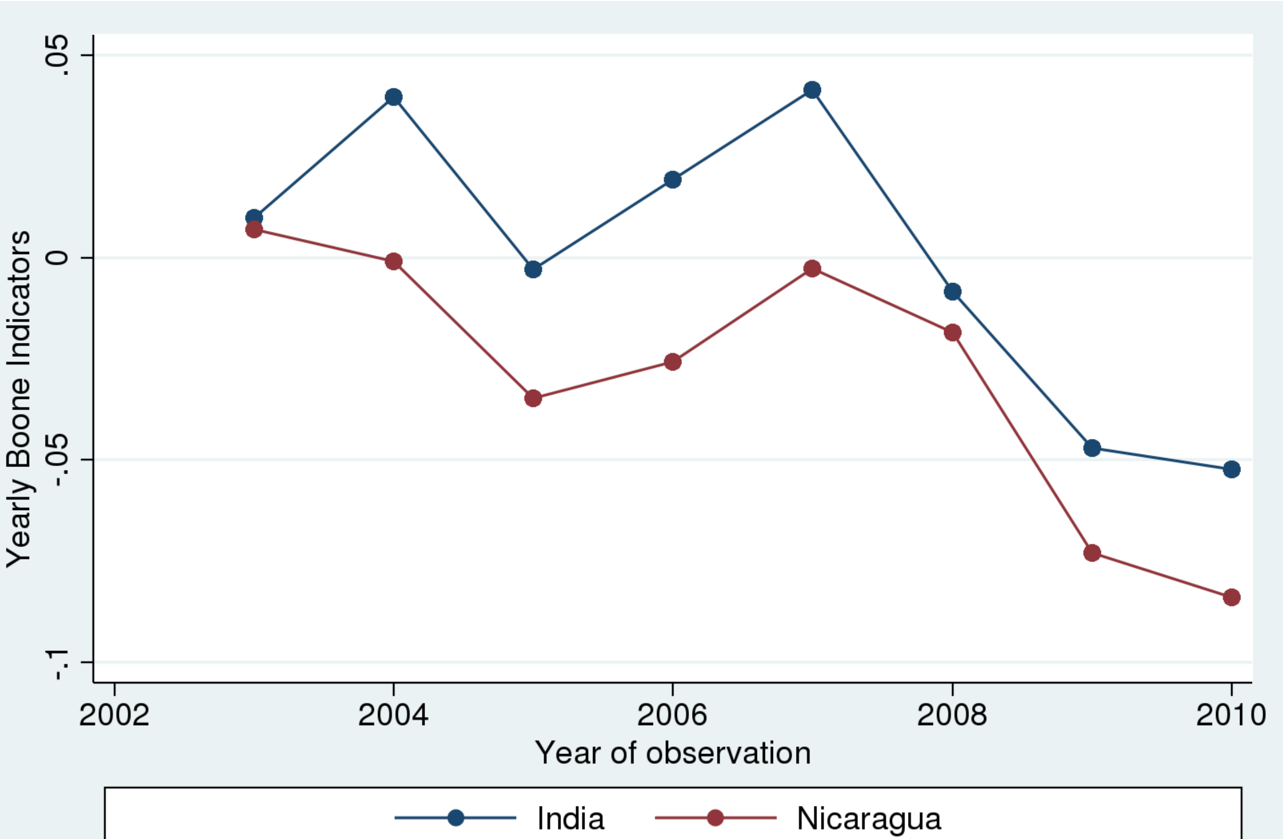

Figure 2: Boone indicators of the countries showing increased competition

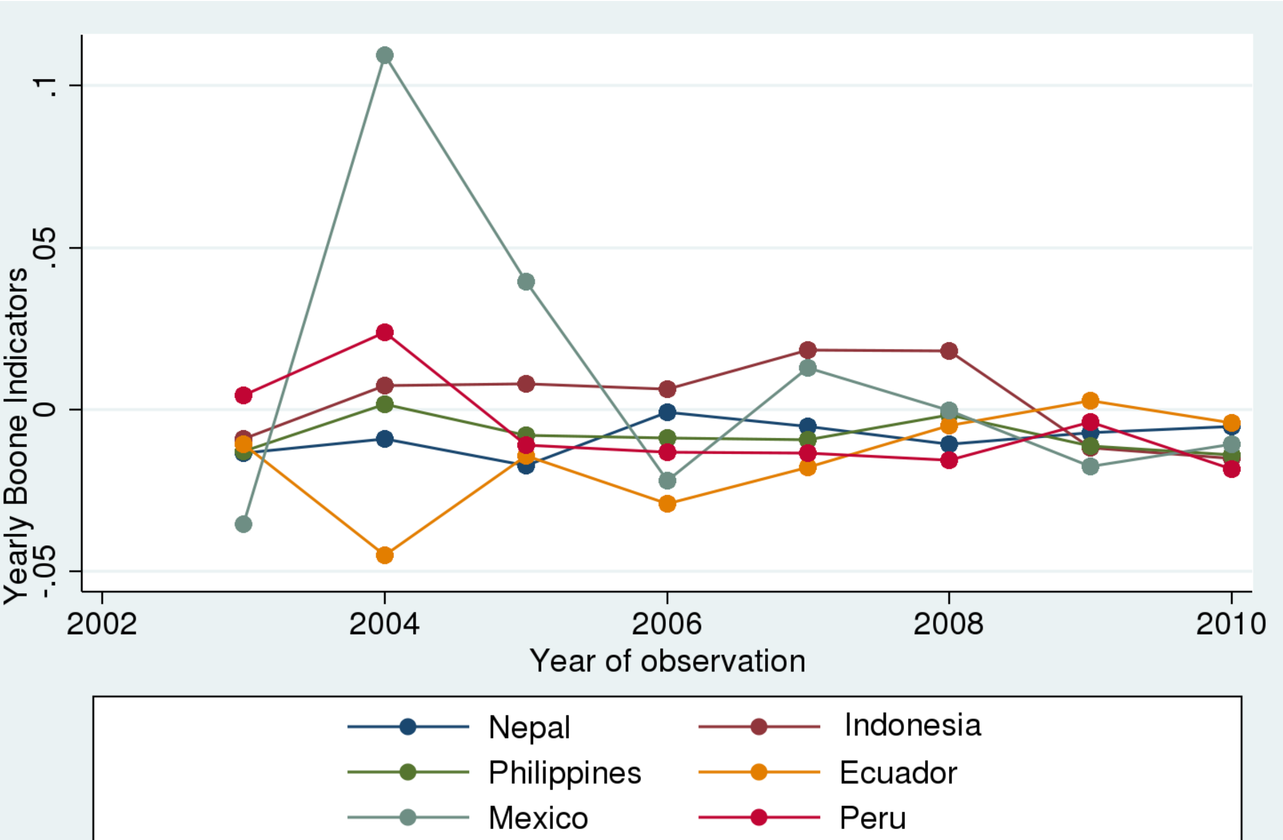

Figure 3: Boone indicators of the countries with no significant change in competitior

Appendix: Estimation for the Translog Cost Function (TCF) for the Boone indicator

Table A1: Estimated Translog Cost Function by Countries

	Bangladesh (BC95)	India (BC95)	Nepal (BC92)	Indonesia (BC95)	Philippines (BC95)
Dependent Variable: Total expenses					
Outputs					
Log (Loans)	1.051***	0.966***	1.145***	0.992***	0.982***
	(0.017)	(0.013)	(0.082)	(0.020)	(0.017)
0.5*Log $(\text{Loans})^2$	0.009	-0.009	0.013	-0.008	-0.000
	(0.007)	(0.007)	(0.048)	(0.008)	(0.014)
Input prices					
Log (PF)	0.216*	0.327***	0.075	0.250***	0.320***
	(0.100)	(0.016)	(0.161)	(0.016)	(0.045)
Log (PPC)	0.568***	0.395***	0.577***	0.402***	0.360***
	(0.059)	(0.073)	(0.111)	(0.030)	(0.048)
0.5*Log $(\text{PF})^2$	0.008	0.133***	0.447**	0.121***	0.133***
	(0.096)	(0.010)	(0.138)	(0.008)	(0.026)
0.5*Log $(\text{PPC})^2$	0.400***	0.172***	0.470***	0.365***	-0.003
	(0.058)	(0.046)	(0.105)	(0.051)	(0.114)
Cross-products between input prices					
Log (PF)*Log (PPC)	0.084	-0.113*	-0.466***	-0.170***	-0.058
	(0.067)	(0.048)	(0.123)	(0.027)	(0.049)
Cross-products between output and input prices					
Log (PF)*Log (Loans)	0.056*	0.031**	-0.115	-0.030**	0.003
	(0.027)	(0.012)	(0.080)	(0.010)	(0.017)
Log (PPC)*Log (Loans)	0.025	-0.007	0.170*	-0.031	0.005
	(0.019)	(0.016)	(0.070)	(0.019)	(0.023)
Control variables					
Constant	-0.507***	-0.523***	-0.501***	-0.401***	-0.365***
	(0.072)	(0.025)	(0.085)	(0.035)	(0.048)
λ	4.678***	62.605***		62.669***	3.559***
	(0.097)	(0.413)		(0.338)	(0.157)
σ_u	0.227*	5.391***		4.195***	0.414*
	(0.111)	(0.408)		(0.332)	(0.163)
σ_v	0.049	0.086***		0.067***	0.116***
	(0.030)	(0.010)		(0.012)	(0.022)
σ-constant			4.417***		
			(0.451)		
γ-constant			8.090***		
			(0.602)		
μ-constant			-341.506***		
			(47.995)		
Log-Pseudo-likelihood	99.018	99.147	20.667	95.685	69.403
Observations	127	359	106	142	319

*BC95: Battese and Coelli (1995) model, BC92: Battese and Coelli (1992) model, PF: Price of funds, PPC: Price of physical capital. * p<0.05, ** p<0.01, *** p<0.00

Table A1: Estimated Translog Cost Function by Countries (contd.)

	Bolivia (BC92)	Ecuador (BC95)	Mexico (TFE)	Nicaragua (BC95)	Peru (BC95)
Dependent Variable: Total expenses (normalised by personnel expenses, one of the input prices)					
Output					
Log (Loans)	1.068***	0.996***	0.808***	1.033***	1.007***
	(0.042)	(0.011)	(0.050)	(0.035)	(0.010)
0.5*Log $(\text{Loans})^2$	-0.012	0.009	0.005	-0.032	0.005
	(0.017)	(0.008)	(0.021)	(0.026)	(0.006)
Input prices					
Log (PF)	0.186	0.353***	0.243***	0.240***	0.322***
	(0.103)	(0.025)	(0.061)	(0.035)	(0.034)
Log (PPC)	0.265***	0.286***	0.386***	0.372***	0.394***
	(0.047)	(0.026)	(0.060)	(0.074)	(0.051)
0.5*Log $(\text{PF})^2$	-0.075	0.105***	0.052	0.064***	0.117**
	(0.124)	(0.014)	(0.030)	(0.016)	(0.040)
0.5*Log $(\text{PPC})^2$	0.996*	0.518***	0.120	0.137***	0.228
	(0.392)	(0.098)	(0.084)	(0.031)	(0.201)
Cross-products between input prices					
Log (PF)*Log (PPC)	-0.083	-0.061*	-0.006	-0.043	-0.052
	(0.126)	(0.029)	(0.046)	(0.044)	(0.083)
Cross-products between output and input prices					
Log (PF)*Log (Loans)	0.062	0.011	-0.022	0.065**	0.017
	(0.050)	(0.015)	(0.021)	(0.024)	(0.023)
Log (PPC)*Log (Loans)	0.083**	-0.007	-0.015	-0.020	-0.032
	(0.028)	(0.016)	(0.045)	(0.050)	(0.027)
Control variables					
Constant	-0.579***	-0.566***	--	-0.529***	-0.465***
	(0.098)	(0.023)		(0.041)	(0.036)
λ		53.026***	0.036	2.094***	9.549***
		(0 .706)	(0.055)	(0.060)	(0.234)
σ_u		3.655***	0.006***	0.156***	0.726**
		(0.701)	(0.002)	(0.040)	(0.230)
σ_v		0.069***	0.169***	0.075**	0.076***
		(0.017)	(0.057)	(0.025)	(0.013)
σ-constant	2.362***				
	(0.343)				
γ-constant	6.048***				
	(0.365)				
μ-constant	-122.074***				
	(12.232)				
Log-Pseudo-likelihood	48.225	137.698	65.177	60.915	160.308
Observations	143	242	180	146	324

*TFE: Greene (2005), True fixed-effects model, BC95: Battese and Coelli (1995) model, BC92: Battese and Coelli (1992) model, PF: Price of funds, PPC: Price of physical capital. * p<0.05, ** p<0.01, *** p<0.00